To Impress an Algorithm: Minoritized Applicants' Perceptions of Fairness in AI Hiring Systems

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Abstract. Technology firms increasingly leverage artificial intelligence (AI) to enhance human decision-making processes in the rapidly evolving talent acquisition landscape. However, the ramifications of these advancements on workforce diversity remain a topic of intense debate. Drawing upon Gilliland's procedural justice framework, we explore how IT job candidates interpret the fairness of AI-driven recruitment systems. Gilliland's model posits that an organization's adherence to specific fairness principles, such as *honesty* and the *opportunity to perform*, profoundly shapes candidates' self-perceptions, their judgments of the recruitment system's equity, and the overall attractiveness of the organization. Using focus groups and interviews, we interacted with 47 women, Black and Latinx or Hispanic undergraduates specializing in computer and information science to discern how gender, race, and ethnicity influence attitudes toward AI in hiring. Three procedural justice rules, *consistency of administration, job-relatedness,* and *selection information*, emerged as critical in shaping participants' fairness perceptions. Although discussed less frequently, *the propriety of questions* held significant resonance for Black and Latinx or Hispanic participants. Our study underscores the critical role of fairness evaluations for organizations, especially those striving to diversify the tech workforce.

Keywords: Algorithms · Hiring · Bias

1 Introduction

Recent studies in information sciences note a rapid shift in decision-making from humans to algorithms in talent acquisition, a trend further supported by human-computer interaction (HCI) research [46, 80, 86]. Organizations are turning to AI-driven platforms like HireVue, Textio, and Ideal for intelligent automation of various talent acquisition tasks, from job advertising and resume evaluation to candidate selection and interviewing [1]. These platforms scrutinize candidates' gestures, linguistic choices, and vocal nuances, comparing them against benchmarks set by other applicants for similar roles to generate "employability scores." The software can sift through vast stacks of resumes and harness disparate data sources to predictively match candidates with suitable positions, refine job descriptions by rectifying inherent biases in language, and deploy bots for interview scheduling [13].

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A 2020 CompTIA survey [95] involving 400 h professionals and corporate officials in the US revealed that 32% have already integrated AI tools for candidate assessment, while 80% anticipate AI significantly reshaping talent acquisition, management, and development. The purported objectivity of these tools, however, is contested by scholars who point to their potential to perpetuate or introduce new biases [12, 41, 62].

Algorithmic biases have profound implications, specifically for historically minoritized groups [62, 65]. We use the term "minoritized" to acknowledge the longstanding marginalization of tech professionals identifying as women, Black or African American, and Hispanic or Latinx. Minoritized underscores the individual agency and resilience while acknowledging the oppressive systems that have shaped their work experiences [15]. According to 2020 data from the USBureau of Labor Statistics [92], the US workforce was predominantly white (78%), followed by Black (12%) and Asian (6%) workers. Latinx or Hispanic individuals, who could belong to any racial category, constituted 18% of the workforce. Women made up nearly half (47%) of the total workforce. However, workforce demographics in the computing and mathematics sectors show greater underrepresentation of women (25%), Black (9%), and Latinx or Hispanic (8%) workers [92].

The urgency to diversify the tech workforce increases with the pervasive influence of AI. West et al. [81] argue AI systems are fundamentally classification technologies designed to differentiate, rank, and categorize. However, the consequences of these classifications are not uniform and often mirror the entrenched societal inequalities. The underrepresentation of technologists from minoritized groups in the design and development process may result in AI systems inadequately trained to discern the nuances of women and people of color [81]. Thus, the tech industry's diversity challenges may be inextricably linked to biases in the AI systems being engineered and deployed.

Our study explores how AI-driven hiring platforms can perpetuate disadvantages for job seekers with minoritized identities. Motivated by the evolving discourse on algorithmic decision-making and fairness, our research is anchored in procedural justice principles, which emphasize the perceived fairness of decision-making processes [9, 27, 45, 73]. Through this lens, we discern the fairness of AI-driven hiring platforms from the vantage point of minoritized undergraduate job seekers in computing majors. Guided by Gilliland's [27] empirical model, which juxtaposes procedural and distributive justice against perceived fairness in hiring procedures, we conducted focus groups and interviews to address two research questions:

1. What factors influence minoritized job aspirants' perceptions of fairness vis-à-vis algorithmic and human decision-making during their job search?
2. How are perceptions of fairness translated into procedural justice rules by minoritized job aspirants?

Understanding the intersection of historical disparities in tech workforce diversity and the potential pitfalls of AI-driven hiring platforms is essential for steering equitable recruitment policies, identifying the inherent biases in algorithmic decision-making, and discerning the implications of AI recruitment on historically marginalized groups [87].

2 Background

The intricate interplay between organizational decision-making processes and individuals' perceptions of these processes has been the subject of extensive scholarly attention, particularly in procedural justice. Seminal works by Thibaut, Walker, Leventhal, and Gilliland provide a foundational understanding of how individuals perceive fairness within organizational contexts. This section presents these foundational theories to provide a theoretical backdrop for our study and underscore the enduring significance of fairness perceptions in organizational contexts.

2.1 From Procedural Fairness to Procedural Justice

Thibaut and Walker [73] were among the early scholars to theorize about an organizational procedure's perceived fairness. Their work underscored the significance of an individual's "voice" or ability to exert control within fairness determinations. They posited that when individuals could influence or provide input into a decision, they were more likely to perceive the process as equitable. This initial perspective mainly focused on the fairness of the decision-making processes; a concept referred to as procedural fairness.

Marking the transition from procedural fairness to procedural justice is the expanded focus on the fairness of the processes and the outcomes and interactions within them. Leventhal's [45] seminal work intertwined procedural justice with equity theory, which birthed the concept of procedural fairness. He constructed six procedural rules: *consistency, bias-suppression, accuracy, correctability, representativeness,* and *ethicality* [27]. Each rule identifies reward allocation methods and an individual's perception of fairness within a given scenario.

Building on these foundational theories, Bies and Moag [8] introduced the concept of interactional justice. This concept focuses on an individual's ability to assimilate and communicate information throughout decision-making processes and emphasizes the decision-maker's behavior during the execution of procedures. This model highlights how individuals perceive treatment throughout these organizational processes [8]. Subsequent research highlights that when individuals confront unfavorable outcomes, providing comprehensive rationales for such decisions can potentially temper the adverse reactions [27, 28].

Through this evolution from Thibaut and Walker's emphasis on the fairness of decision-making processes to Leventhal's integration of outcomes and further to Bies and Moag's focus on interactional aspects, the concept of procedural fairness has broadened into procedural justice. This shift occurred because of a deeper understanding of the myriad factors contributing to individuals' perceptions of justice in organizational contexts, recognizing that fairness extends beyond mere processes to encompass outcomes and interpersonal interactions.

2.2 Gilliland's Procedural Justice Rules

Gilliland's framework connects procedural fairness theories to the foundational elements of well-established organizational justice research. This research encompasses studies on managerial fairness [68], the nuances of communication fairness during recruitment processes [9], the intricacies of allocation decisions [45], the dynamics of performance appraisals [28], and the norms governing interactional justice [78]. Drawing from these theories, Gilliland distills ten procedural justice rules, which are further grouped into three overarching categories: formal characteristics of procedures, the explanations provided during these procedures, and the interpersonal treatment experienced by individuals. For a detailed list of these rules and their associations with organizational justice theories, refer to Table 1. The subsequent sections describe these categories and their associated rules.

Formal Characteristics capture the foundational aspects of the hiring process, including:

1. **Job Relatedness**: The relevance of a selection test in assessing an applicant's knowledge pertinent to the job [45].
2. **Opportunity to Perform**: The chance for an applicant to provide input or showcase competencies, influencing their perception of the process's fairness [63].
3. **Reconsideration Opportunity**: Providing a second chance for applicants to influence decision-making, thereby enhancing perceived fairness [28, 62, 68].
4. **Consistency of Administration**: Ensuring uniformity in the selection mechanism or assessment across candidates, promoting equitable outcomes [50, 57, 62].

Explanation delves into the clarity and transparency of the hiring process. This domain comprises:

1. **Feedback**: The significance of providing candidates with feedback on their performance, which influences their overall perception of the process [50, 57].
2. **Selection Information**: The clarity and validity of the information provided to candidates about the selection process, which is rooted in interactional justice literature [28, 62].
3. **Honesty**: The importance of sincerity and truthfulness in the hiring process is especially crucial given the proprietary nature of many AI algorithms [9].

Interpersonal Treatment focuses on the human aspect of the hiring process, emphasizing:

1. **Interpersonal Effectiveness of Administrator**: Treating candidates with warmth and respect influences their overall perception of the organization and the process [23].
2. **Two-way Communication**: The significance of allowing candidates to provide input is especially relevant in AI-driven interviews [48].
3. **Propriety of Questions**: The importance of ensuring questions are appropriate and devoid of discriminatory overtones, maintaining the integrity of the process [2].

Lastly, Gilliland hints at **Potential Additional Procedural Rules** that might not strictly fit within traditional organizational justice literature but are relevant in the modern context. These include the ease with which candidates can fake answers during interviews [27] and concerns about the invasiveness of questions or procedures [2, 27, 86]. This comprehensive categorization offers a structured lens to evaluate the fairness of AI-driven hiring processes, ensuring they align with established principles of procedural justice. These perceptions of fairness can significantly influence an applicant's interview experience, skills assessment, and subsequent hiring decisions.

Table 1. Relationships Among Procedural Rules and Organizational Justice Theories

Procedural Rule	Organizational Justice Theory
Formal Characteristics	
Job relatedness	Accuracy rule [45], Representativeness [68]
Opportunity to perform	Voice [73], Soliciting input [28], Resource [68]
Reconsideration opportunity	Ability to modify rule [45], Ability to correct [68], Ability to challenge [28]
Consistency of administration	Consistency rule or standard [28, 45, 68, 77]
Explanation	
Feedback	Timely feedback [77], Timeliness [68]
Selection information	Information [68], Communication [68], Explanation [77]
Honesty	Truthfulness [10]
Interpersonal Treatment	
Interpersonal effectiveness	Respect [10]
Two-way communication	Two-way communication [28], Consider views [77]
Propriety of questions	Propriety of questions [10], Personal bias [45], Bias suppression [68, 77]

2.3 Procedural Justice and Algorithmic Fairness in Hiring

The landscape of employment selection has evolved significantly with the advent of technology, leading to many studies examining job applicants' reactions to these technology-enabled methods [5, 7, 16, 31, 40, 42, 61, 71, 72]. A comprehensive review of over 145 studies reveals that applicants' responses are pivotal in shaping their beliefs, intentions, and subsequent behaviors [49]. These responses offer invaluable insights into the facets of the talent acquisition process that might influence perceptions of fairness [72]. However, with the rise of AI-driven talent acquisition tools, there is a pressing need to apply these established models and techniques in empirical studies.

For example, how individuals perceive algorithmic decisions compared to human judgments remains an area ripe for exploration [44]. Scholars posit that the unique capabilities of AI-driven hiring tools might establish a hierarchy of justice attributes. Understanding this hierarchy could be instrumental in designing HR practices and technologies that champion fairness [19]. Furthermore, specific task factors might shape individuals' perceptions of fairness, reactions, and trust in algorithmic decision-making [44].

While fairness, trustworthiness, transparency, and bias have become focal points in procedural justice research [37, 43, 44], the voices of communities that may experience the most significant harm must be included, understood, and valued. Companies' increasing reliance on algorithms, driven by the allure of cost savings, task automation, and remote decision-making capabilities, necessitates a deeper understanding of potentially disparate impacts on minoritized groups [37, 43]. Lee [44]'s investigation into decision-making tasks, whether executed by algorithms or managers, offers an initial understanding. While participants perceived both entities as fair in mechanical tasks, the algorithm's judgments on more human-centric tasks were deemed less trustworthy and fair compared to human managers [44]. However, additional studies have found that participants are more inclined to accept algorithmic decisions when provided with transparent insights into the decision-making process [43].

Furthermore, AI hiring platforms are adept at integrating conventional employment data, such as resumes and performance metrics, with multifaceted data streams like audio, video, text, and even social media posts. This amalgamation facilitates the creation of comprehensive psychological profiles of candidates. A looming concern arises when algorithmically generated profiles are used as benchmarks to gauge organizational fit or predict a candidate's potential job performance. There is a tangible risk that individuals from diverse cultural backgrounds might find themselves at a systemic disadvantage, potentially perpetuating biases rather than mitigating them [87].

3 Methodology

In this study, we conducted focus groups and interviews with participants from a US university, specifically targeting undergraduate students pursuing majors in computer and information sciences. Our recruitment strategy aimed to engage students who identified as minoritized by race and/or gender. Of the students approached, 47 agreed to participate in our study. Most participants were nearing the end of their undergraduate journey, with 51.1% (n = 24) in their third to fifth years. While no students identified with non-binary gender identities, 78.7% identified as female, and 21.3% identified as male. In terms of ethnicity, the majority identified as African American or Black (46.8%), followed by White (36.2%), Asian (12.8%), and Latinx or Hispanic (4.3%).

3.1 Focus Groups

The 47 participants were divided into two sessions: one with 23 participants and the other with 24. Focus group sessions, spanning 75 to 90 min, were audio-recorded and transcribed to preserve participants' genuine sentiments and perspectives. Two researchers oversaw both sessions to ensure comprehensive data collection and observation.

To establish a common foundational understanding, we began each session by providing participants with a definition of algorithms, framing them as "processes or sets of rules that a computer follows in calculations or other problem-solving operations." Next, participants were shown a video detailing the workings of AI hiring software. This video served as a primer, explaining how such software operates, its potential applications, the spectrum of businesses leveraging this technology, and a deep dive into a specific AI hiring platform, Hirevue.

Post-video, participants were presented with one of two scenarios:

1. An individual seeks a programming position, and an algorithm curates a list of job opportunities based on the search criteria. Or,
2. An individual pursuing a programming role presents their resume to a manager at a college career fair. The manager then outlines the available positions aligning with the individual's qualifications.

Upon reflecting on their respective scenarios, participants completed a questionnaire. The session concluded with a group discussion where participants shared their responses to the scenarios. The questionnaire and discussion prompts were designed to elicit participants' perceptions of fairness, as exhibited by both the algorithm and the manager, and to elucidate the rationale behind their responses.

3.2 Interviews

After the focus group sessions, we embarked on a series of follow-up interviews with a subset of ten participants. These interviews, which ranged from 22 to 35 min, were semi-structured. The primary objective was to investigate participants' perceptions and firsthand experiences concerning algorithmic hiring. The structure allowed for pre-determined questions and the flexibility to explore emergent themes and insights.

3.3 Analysis

We employed an inductive approach to analyze the transcripts from focus groups and interviews. Thematic coding allowed us to extract meaningful themes aligned with critical areas of research interest: participants' familiarity with AI hiring platforms, their sentiments towards these systems, preferences between traditional and AI-driven interviews, their grasp of the underlying mechanisms of AI hiring tools, and discussions surrounding accent, cultural nuances, skin tone, and personal identity. We also identified participants' strategies for enhancing their performance in AI-mediated interviews and their perceptions of companies that leverage such algorithmic hiring tools. Analyzing the transcripts, we iteratively refined and organized themes into categories. A significant aspect of our analysis was identifying procedural justice rules, as articulated by our participants.

4 Findings

This section presents five themes from our data analysis and the procedural justice rules participants identified as significant throughout the recruitment process. To differentiate between the data sources, we have used the abbreviations "FG" for focus group sessions and "I" for interviews, followed by the respective participant numbers (e.g., FGP01 and IP01).

4.1 Theme 1: Previous Interactions with AI Recruitment Systems

Most participants in their third, fourth, and fifth year of study had encountered AI-driven recruitment platforms, encompassing tools for resume screening, video interview recording, and coding challenges. Despite availing themselves of the professional development resources offered by the university's career coaches, participants reported that the training was limited because they encountered a variety of hiring platforms and inconsistent hiring procedures. This variation was particularly evident in the guidance given to applicants before the interview and the interview protocols that facilitate the applicant's engagement with AI hiring platforms.

For instance, unclear pre-interview instructions compelled participants to devise strategies for interfacing with the platform during their interview. One participant, IP01, shared their experience with HireVue: "So for HireVue, they just gave me a link, and then I went to the link…I did a demo recording, made sure that everything was fine, and then after that, they gave me some kind of prompt, kind of like questions, and I had to record my answers. So I think it was around like two minutes each for each of those questions…".

The interview's duration and format varied among participants, making it difficult to develop strategies to navigate these platforms. IP01 further elaborated on the time constraints of their interview, stating, "I think it was probably being like 15 to 20 min in total…".

In contrast, FGP14 experienced a variety of interview structures: "My interview had two different types of video recordings that you would do. Some of the questions were timed, and you only had a specific amount of time to answer a question, and then there were some which you had an unlimited number of attempts…" This variation in interview structure underscores the need for flexible strategies when preparing for AI-based interviews.

IP02 experienced a longer interview duration: "The interview session lasted…about 40 min or so, and I had to answer 15 questions." This response highlights the potential for significant differences in the time commitment required by different AI interview platforms.

Most participants encountered two or three hiring platforms during their job search. IP08, for example, shared their experience where the AI tool served as a conversational partner: "…they also sent me one where it was like, it was like a phone screen, but I'm talking to an automated bot instead of another person." This example illustrates the diverse ways in which AI is integrated into the hiring process.

4.2 Theme 2: Fairness of Resume Screening

Most participants agreed that the fairness of resume evaluation is comparable, whether conducted by a human or an algorithm, when discussing automated resume reviews. FGP07, for instance, posited, "I actually thought that the resume review might be the same either way, based on the fact that I think most companies are just looking for some pretty basic information from your resume…" Other participants perceived the automated resume screening process as advantageous, enabling organizations to review more resumes and potentially enhancing their employment prospects. IP01 elaborated on this point, stating, "…I would be like, [to be] called to give an interview, let's say essentially, they were screening, let's say five, people without this tool, maybe now they can scale to 10. So, I would get like more opportunity to… express…[my] views and answers."

Other participants echoed this sentiment. IP07 noted, "So… if this platform allows me to get more interviews in the future… because they see it as a good option too… as like a screening tool, I'm okay with that because it gives me more chances." Participants attributed the source of these additional opportunities provided by AI platforms to keyword identification in resumes. As IP03 explained, "I might use some AI… to pick out keywords from resumes…" This quote highlights the potential for AI to enhance the efficiency and breadth of the resume screening process.

4.3 Theme 3: Possibility of Bias

The topics of race, culture, and identity were prominent throughout the focus groups and interviews. Many of our participants expressed apprehensions about the possibility of bias influencing their prospects of securing a particular role. IP03, for instance, raised concerns about the system favoring homogeneous candidates: "Um, but then you also have candidates who are strong in technical skills but not great with these online video platforms. Um, so it really biases the system towards people who are able to fit the mold, um, just because it's what the system looks for rather than prioritizing kind of the best candidates for the company itself."

FGP08 highlighted the potential for overlooking valuable soft skills that may not be immediately evident in written form: "So, sometimes a person may not come with the right written things, but if I'm talking, you can pick up on different soft skills that they might have that you didn't think that your company needed, so they could be overlooked because it wasn't like you said, those small dimensions being filled."

During virtual interviews, participants also raised concerns about potential bias related to the lighting conditions or the background of a workspace. FGP06 stated, "So, the thing is, I feel there's a lot you have to consider when doing a virtual interview or something like that. You need to consider lighting, what you're wearing, the background, things that are in the background, and it's more that you have to take into consideration."

However, not all participants believed that AI hiring platforms inherently favor bias. Some saw the potential for these platforms to alleviate bias concerns. IP02 suggested, "An interviewer that has some…racial bias might not be prone to hiring certain people, representatives of, [a] certain races or same thing with gender…That could be a problem. And, those interview tools, I think, could help."

While this viewpoint was not widely shared among our participants, it underscores the complexity surrounding the use of AI in hiring platforms. The potential for bias, whether mitigated or exacerbated by AI, remains critical in these tools' ongoing development and deployment.

Racial, Cultural, and Identity Bias

Participants expressed apprehension about potential racial, cultural, and identity biases that could hinder their interview progression. Specific personal attributes were highlighted as potential issues, with several individuals citing their unique skin tones and speech patterns as possible variables the algorithm could misinterpret. FGP01, for instance, expressed concerns about skin tone: "…I have a different skin tone than the guy that was on the screen, so my emotions may not show the same that the algorithm is looking for if that makes sense." FGP03 expanded on this, pointing to cultural differences: "Yeah, in addition to facial recognition, I also think that if you come from a different society, cultural background, your reactions aren't the same as what they are probably measuring…".

Participants of color further noted how racial differences require attention to prepare for AI-based interviews adequately. IP03, for instance, shared a common struggle: "I found it challenging to ensure my face was clearly visible and well-lit in the video. Setting up the right lighting conditions was often a struggle." This quote highlights the unique challenges posed by video-based AI interview platforms, which require considerations beyond traditional interview preparation. IP09 voiced concerns about the potential for bias in AI systems, citing specific examples: "I think over-reliance on these tools can be detrimental as they can introduce a certain level of bias. I have read articles about how Amazon's facial recognition has shown bias towards people of color…".

Participants also expressed concerns about the potential for unique characteristics to be overlooked by an algorithm not designed to recognize such diversity. FGP08 noted, "I think algorithms also miss out on uniqueness." Personal experiences became particularly relevant to these concerns, especially when individuals were compared with other candidates. The lack of transparency in how these comparisons are made was frustrating. FGP10 questioned the objectivity of these comparisons: "..I did interview with a company that used HireVue, and particularly when you were talking, it made me think about things, about the way you say that the algorithms are comparing the candidate to the people that might be experts or ideal candidates in that profession, it becomes objective because it's like, 'What is the perfect candidate?'".

4.4 Theme 4: Necessity for Human Interaction

The dialogue comparing human interviews with AI interviews predominantly underscored the necessity for human interaction. Participants also expressed concerns about the algorithm's autonomy in decision-making without human oversight or intervention. The reasons for preferring in-person interviews over AI varied among our participants, ranging from the potential for personal connection, the opportunity to glean crucial information about the organization during an in-person interview, and assessing workplace compatibility. FGP21 encapsulated this sentiment: "But I don't really like the idea that it can all be the machine, and the human gets zero say in it."

Preference for In-Person Interviews

Our participants overwhelmingly favored some form of human or in-person interviews. They frequently discussed the potential to increase their chances of success by showcasing their personality and establishing a rapport with the interviewer, a connection they felt could not be formed with an algorithm.

IP03, for instance, stated, "I really do like a company that values human interaction, where they value being able to talk to you face-to-face… Kind of get to know you as a person." Similarly, IP08 expressed, "…but on the other hand, I do miss out on that face-to-face interaction, which I think I perform better at." IP02 added, "…when you're talking to a person, you get to see their interviewer's mentality and…you can frame your answers in a way that would be better suited for that particular person."

During the interviews and focus groups, most participants agreed that human interaction was necessary if an organization utilizes algorithms during talent acquisition. They also mentioned the value of receiving information from the interviewer that could aid their decision-making. FGP03 noted, "…managers ideally have the best information when it comes to what their company's culture is looking for and how that person might fit into your company. That's something you may not be able to tell straight off an algorithm…".

Trust in the Algorithm

Only a few participants pointed to a trust issue they could not overcome. They voiced their concerns about the proprietary or "black box" technology and the lack of transparency in the algorithm's decision-making process. FGP05 expressed, "…You just can't trust them… I think that there still needs to be some type of human interaction." IP10 added, "I don't totally trust them. I do have some trust beforehand, but then that trust is limited…".

While only a small number of our participants addressed this issue of trust, it may become more prominent as AI continues to permeate other industries.

4.5 Theme 5: Necessity for Training

Participants underscored the importance of disseminating knowledge about these algorithms across academic institutions. Despite their active engagement with career counselors and regular participation in professional development activities offered by career services and corporate partners, they expressed uncertainty about their preparedness for AI hiring systems. Overall, participants agreed that training would be beneficial, as would the opportunity to practice AI interviews, like preparing for an in-person interview. Participants recommended three additional areas for career preparation:

1. IP02 suggested the development of training modules: "I think it would be helpful… I'm sure this 'black box' technology will continue to develop, and there will likely be online training modules offered to people to practice…"
2. FGP09 pointed out the need to understand what the algorithms are looking for: "…If you haven't done enough video interviews and don't understand what they're looking for, such as facial movements, an algorithm isn't taking that into account when searching for the right applicant for the job."
3. Participants also felt that career counselors needed additional training on algorithmic hiring processes. IP03 stated, "I do think that career offices definitely need to stay up-to-date with how recruiting happens in the real world. If there were sessions about how to navigate and succeed with these video platforms, I would have definitely attended."

4.6 Significance of Procedural Justice

Consistency of administration and *job-relatedness* were the two procedural justice rules most positively associated with participants' perceptions of fairness in AI hiring. Participants' understanding of job-relatedness was based on their experiences with LinkedIn, where the algorithm analyzes skillsets and resumes and recommends suitable job opportunities. FG12 noted, "The algorithm could be super spot on or suggest a job that has nothing to do with your field." While "algorithms could be a bit off" (IP04) in their job recommendations, they mitigate the risk of human biases in job referral networks where job leads "depend on who you know" (IP07). Skills assessments via an algorithm were generally considered fair because "you either know how to code or you don't" (FG03). In contrast, the *opportunity for reconsideration* was consistently viewed as unfair when decisions were made solely by algorithms without human oversight.

The explanation category of procedural justice rules, *Selection Information, Honesty, and Feedback,* was mentioned frequently and viewed negatively by participants when delivered from an automated system. As IP10 noted, "It does not feel as great to be rejected by a computer based on code - it is cut and dry to find out the results." Similarly, positive feedback from an algorithm was not well received. FGP20 explained, "…it would be more meaningful…hearing that from an individual who wants you in that environment, versus pretty much saying that you ticked all the boxes." These quotes may also explain why procedural justice rules in *Interpersonal Treatment*, like *two-way communication* and *interpersonal effectiveness of the administration*, were viewed negatively and discussed with the least frequency.

The *propriety of questions* was particularly salient for Black and Latinx/Hispanic participants considering potential harm during automated video interviews. These participants discussed how exclusions in training data sets led to unfair outcomes. Thus, an automated video interview "adds an extra layer of things you have to do" (FG06) because "in most cases when they make these programs, minorities are most likely not the default" (IP09). As FG07 noted, "We are being compared to people who we are nothing like."

5 Discussion

5.1 Conceptual Implications: Bridging Procedural and Distributive Justice

The landscape of AI-driven hiring is rapidly evolving, and our study offers a fresh perspective by focusing on the perceptions of aspiring technology professionals from historically underrepresented groups. This emphasis on women, Black, and Latinx or Hispanic undergraduate students in computing fields provides a richer understanding of the complexities surrounding the fairness of AI hiring systems, especially when viewed through the lens of procedural justice rules.

Our findings resonate with the broader literature on procedural justice, which has long been concerned with the fairness of decision-making processes [80, 82, 84]. However, our research introduces a novel dimension by emphasizing the intricate interplay between procedural and distributive justice. Distributive justice, as defined, revolves around the perceived fairness of allocations or, in this context, the outcomes of hiring decisions. When participants evaluate AI hiring systems, they assess the fairness of the process (procedural justice) and the fairness of the outcomes (distributive justice). Their concerns about discrimination and performance expectations, rooted in racial and gender stereotypes, can reflect their perceptions about the fairness of the outcomes they anticipate from these systems.

The role of identity emerges as a pivotal factor in shaping these perceptions. While procedural justice rules provide a framework for understanding fairness, our participants' lived experiences and identities add depth. The intersection of identity with procedural and distributive justice nuances the discourse and suggests that fairness perceptions are multifaceted and deeply personal. Algorithmic biases, as highlighted by our participants, further complicate this narrative. While algorithms designed with an emphasis on learning about underrepresented groups can potentially lead to more equitable outcomes, as Li et al. [46] suggested, the perceived fairness of these algorithms is contingent upon their transparency and adaptability. This observation underscores the importance of exploration in the hiring process, ensuring that AI systems are technically fair and perceived as such by diverse job seekers.

As expressed by our participants, the indispensable role of human interaction in the hiring process offers another layer of complexity. While AI systems can efficiently match candidates to job opportunities, the human element—characterized by empathy, understanding, and personal connection—remains irreplaceable. This sentiment aligns with the broader discourse on the limitations of AI and the enduring value of human judgment and interaction.

Our empirical findings underscore that fairness perceptions oscillate across the talent acquisition process. While algorithmic decision-making was perceived as advantageous during job sourcing and skills assessment, AI-mediated interviews were overwhelmingly deemed problematic and unjust. A yearning for human interaction emerged, with a pronounced preference for traditional face-to-face interviews over their AI counterparts. Notably, three procedural justice rules, *consistency of administration*, *job-relatedness*, and *selection information*, emerged as critical in shaping participants' fairness perceptions. Though less frequently cited, the *propriety of questions* held significant resonance for Black and Latinx/Hispanic participants.

In synthesizing these insights, our study beckons a deeper exploration into the theoretical underpinnings of AI hiring. It calls for a holistic understanding that integrates procedural justice, distributive justice, and the unique experiences of underrepresented groups, ensuring that the development and deployment of AI hiring systems are both fair and perceived as such.

5.2 Operational Insights: Navigating AI in Modern Recruitment

The insights derived from our study have profound practical ramifications for the evolving landscape of hiring practices in the age of AI-driven recruitment. The apprehensions voiced by participants about the fairness of AI hiring mechanisms underscore the pressing need for clarity in their deployment. Organizations must take the initiative to elucidate the inner workings of these systems, detailing the decision-making processes. Organizations can foster trust and assuage concerns about potential biases or unfairness by demystifying the role of AI, the criteria it employs, and the extent of human intervention.

Our participants' preference for human interaction in the interviewing process signals a clear message to organizations. While AI can streamline certain aspects of recruitment, the human element remains irreplaceable. A balanced approach might see AI tools handling preliminary screening, with human recruiters stepping in during the more nuanced stages of recruitment. This hybrid model could address both efficiency and the innate human desire for connection.

The study underscores a glaring gap in the current preparation of job seekers, especially those from underrepresented backgrounds, to navigate the intricacies of AI-driven hiring. Academic institutions, in collaboration with industry partners, should spearhead initiatives like workshops on AI interview preparedness or strategies for effective self-presentation in automated settings.

Feedback from our participants points towards the necessity of a more inclusive design philosophy for AI hiring tools that actively seek diverse input, rigorous testing of algorithms against varied datasets, and a commitment to elucidating decision-making processes for end-users.

6 Conclusion

By employing Gilliland's procedural justice rules, we understand the perceptions of fairness in hiring, particularly from the vantage point of minoritized undergraduates pursuing degrees in computer and information sciences. Our study underscores the critical role of fairness evaluations for organizations, especially those striving to achieve diversity benchmarks. To truly champion diversity, equity, and inclusion, algorithms must transcend traditional assessments of fit. Instead, they should recognize and value diverse job-seekers' talents and merits. Such a shift would align with the professed commitments of tech firms to inclusivity and foster a more equitable hiring landscape. Furthermore, it is incumbent upon university career services to evolve, offering tailored guidance on navigating the intricacies of AI-based talent acquisition platforms. Such training would better equip and enhance the marketability of minoritized job-seekers in an increasingly algorithmic hiring ecosystem.

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